



Impacts of climate change on urban rainwater harvesting systems

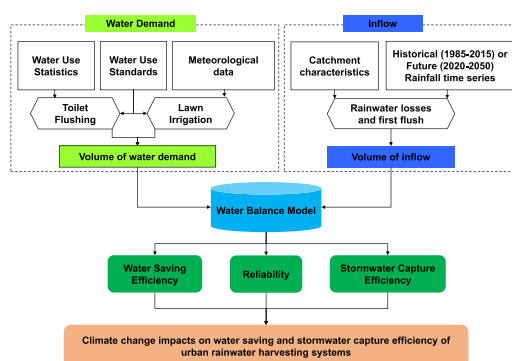
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HIGHLIGHTS

- Impacts of climate change on rainwater harvesting (RWH) are investigated.
- Water saving and stormwater control performances are evaluated.
- A Markov chain-based downscaling technique is evaluated and employed.
- Four climatic conditions and two water use scenarios are considered.
- Performance curves are developed for RWH design & evaluation.

GRAPHICAL ABSTRACT



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ABSTRACT

Rainwater harvesting (RWH) is promoted in many cities (e.g., Beijing and Shenzhen) as a climate change adaptation measure to relieve urban water supply and drainage pressures. In this study, the impacts of future climate change on water saving and stormwater capture performances of RWH systems at cities across four climatic zones of China are investigated. A downscaling technique based on the Climate Generator is evaluated and employed to generate future (2020–2050) daily rainfall data. Performance indices of RWH systems (i.e., water saving efficiency, reliability, and stormwater capture efficiency) calculated using both the future and historical (1985–2015) daily rainfall data are compared. Two water demand scenarios (i.e., lawn irrigation and toilet flushing) are included in the investigation. The water saving performance is positively affected by the increases in future rainfall at the four cities, while the stormwater capture performance is negatively affected as a larger tank size is required to achieve a desired stormwater capture efficiency in the future period. The responses of water saving and stormwater capture performances of RWH systems to climate change are varying with not only the system dimensions (i.e., storage capacity and catchment area), but also the water demand scenarios and locations. RWH systems with larger storage capacity for larger water demand scenarios at humid and semi-humid cities is expected to be more resilient to climate change. The various changing patterns of the performance indices highlight the importance of incorporating climate change in the design of RWH systems. Location-specific adaptive adjustments (e.g., adjusting tank sizes, catchment areas or water demand rates) need to be adopted so that RWH systems can sustainably meet water saving and stormwater control requirements under future climate conditions.

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1. Introduction

Rainwater harvesting (RWH) played an important role in ancient civilizations, especially in drier environments. In recent decades, it has

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been promoted in many regions to address the increasing water supply pressures associated with population growth, urbanization, industrial development and climate changes (Amos et al., 2016; Campisano et al., 2017). For example, several countries (e.g., Australia, China, and Jordan) have mandated the implementation of RWH in new buildings (Abdulla and Al-Shareef, 2009; Imteaz et al., 2011; Jing et al., 2017). Even countries with good water balance conditions (e.g., Brazil, Germany, France, Italy, South Korea, UK, and USA) between demand and available water resources are also promoting RWH to increase the water self-sufficiency of cities (Ghisi et al., 2007; Kim and Yoo, 2009; DeBusk et al., 2013; Melville-Shreeve et al., 2016; Palla et al., 2017).

RWH systems collect rainwater generated from contributing areas such as rooftops, terraces, and courtyards during rainfall events, and store it in cisterns or tanks to supply water for indoor or out-door demands (Fernandes et al., 2015; Jing et al., 2017). Harvested rainwater can be used to replace tap water for non-potable (e.g., terrace cleaning, car washing, toilets flushing, laundry, garden irrigation) or potable (e.g., drinking and cooking) uses (Ghisi et al., 2007; Morales-Pinzón et al., 2014; Lim et al., 2015; Campisano et al., 2017; Pavolová et al., 2019). These uses can account for 80–90% of overall household water consumption in cities (GhaffarianHoseini et al., 2016), therefore, installation of RWH systems can bring significant water saving benefits and alleviate urban water supply pressures (DeBusk et al., 2013; Silva et al., 2015).

RWH also belongs to the large family of detention-based, source control stormwater management strategies such as the Low Impact Development (LID), the Sustainable Drainage System (SuDS), the Water Sensitive Urban Design (WSUD), and the Sponge City (Kim et al., 2012; Litofsky and Jennings, 2014). Implementation of RWH could reduce both volumes and peaks of urban runoff, alleviate pressure of urban drainage systems, and mitigate environmental impacts of urbanization on receiving water bodies (Burns et al., 2015; Palla et al., 2017).

Stormwater management and water saving performances of RWH systems are largely determined by site conditions such as rainfall and contributing areas (Imteaz et al., 2011), tank sizes (Jing et al., 2018), and water demands (Ward et al., 2012). Incorporating water demands and tank sizes with local climate conditions can improve the stormwater management and water saving efficiency of RWH systems. Therefore, design of RWH systems is generally concerned with determining the optimum tank size to ensure water supply and stormwater management performance for the anticipated water demand under local rainfall conditions (Amos et al., 2016; GhaffarianHoseini et al., 2016). Modelling tools and methodologies have been developed over the last 20 years to facilitate the design and/or evaluation of RWH systems, for instance, the design storm approach, continuous simulations, analytical probabilistic approach, stochastic approach, linear programming approach, and nonlinear metaheuristic algorithm (Guo and Baetz, 2007; Kim and Yoo, 2009; Jing et al., 2017).

Local rainfall is one of the major variables of interest in the design and evaluation of RWH systems (Amos et al., 2016; GhaffarianHoseini et al., 2016; Andrade et al., 2017), as it determines the amount of collectible rainwater generated from a given contributing catchment. For most of previous studies, design and evaluation of RWH systems were based on historical rainfall data (Ghisi et al., 2007; Imteaz et al., 2011; Litofsky and Jennings, 2014; Silva et al., 2015; Jing et al., 2018). From these studies, however, RWH users can not get adequate insights of the expected performances of RWH systems regarding future rainfall conditions in the context of climate change (Piao et al., 2010; Zhang et al., 2018). A trend towards more uneven distribution of precipitation has been detected both spatially (Held and Soden, 2006; Chou et al., 2009) and temporally (Chou et al., 2013) at the global scale. During 1951 to 2011, precipitation increased in most areas of China (Zhao et al., 2018). In the early period of this century (2011–2040), a remarkable increase of precipitation in northwestern and northeastern China is expected, while the precipitation appears to decrease in the southern parts of China (Xu and Xu, 2012). Increases in rainfall is also expected in the

future period for other Asian countries such as South Korea (Youn et al., 2012) and Sri Lanka (Lo and Koralegedara, 2015).

With the realization that using historical rainfall data may not accurately size or evaluate RWH systems for the possible future rainfall conditions, several recent studies have used stochastically-generated or General Circulation Models (GCMs) projected rainfall data to assess RWH system performances and create design cases (e.g., Lo and Koralegedara, 2015; Wallace et al., 2015; Haque et al., 2016; Almazroui et al., 2017). However, these studies considered only the water saving objectives of RWH systems, without taking into account the stormwater management performance of RWH systems. Moreover, research on climate change impacts on RWH is still limited as the trends and extents of rainfall vary considerably from regions to regions.

The objective of this study is to investigate the impacts of future climate change on both stormwater volume control and water saving performances of RWH systems for two water demand scenarios in four climatic zones of China. GCMs projected future monthly rainfall at grid scale is downscaled to daily rainfall at four stations using a downscaling technique based on a first-order, two-state Markov chain-based climate generator. A water balance model is developed to calculate the water saving efficiency, reliability and stormwater capture efficiency of RWH systems with the future (2020–2050) and historical (1985–2015) daily rainfall data as input. The impacts of climate change on RWH systems are revealed by comparing and analyzing the changing patterns in water saving efficiency, reliability and stormwater capture efficiency of RWH systems between the future and historical periods.

2. Methods

2.1. Study site and data

As shown in Fig. 1, four provincial capital cities (i.e., Yinchuan, Urumqi, Beijing, and Fuzhou) located in four different climatic zones (i.e., arid, semi-arid, semi-humid and humid, respectively) of China are selected. These four cities are expected to have different rainfall change patterns in the near future (Xu and Xu, 2012). Daily rainfall data of the four cities from 1960 to 2015 are obtained from the National Climatic Centre (NCC) of China (<http://www.climatechange-data.cn/>). The mean annual rainfall depth (1960–2015) ranges from 186.0 mm in Yinchuan, 273.0 mm in Urumqi, 587.2 mm in Beijing to 1351.2 mm in Fuzhou. Wet and dry seasons can be separated based on the mean monthly rainfall at the four cities (Fig. 2). The wet season of Beijing and Yinchuan is from May to October, and that of Fuzhou and Urumqi is from April to September.

GCMs projected monthly coarse rainfall data are also obtained from the NCC of China, which collected outputs of 21 GCMs (Appendix A) participating in the phase five of the Coupled Model Inter-comparison Project (CMIP5), interpolated the outputs onto $1^\circ \times 1^\circ$ grids, and produced the arithmetic ensemble mean of the outputs under three Representative Concentration Pathways (i.e., RCP2.6, RCP4.5, and RCP8.5). Details about the data processing procedure can be found in Xu and Xu (2012). The integrated outputs of the 21 GCMs are used in this study to reduce uncertainty in climate projections resulting from structural differences in the GCMs, as well as uncertainty due to variations in initial conditions or model parameterizations. Using the average GCM outputs is also expected to prevent extreme rainfall outliers from affecting the dataset, while also capturing the erratic nature of climate patterns for more conservative system design. However, it is also possible that the differences among future rainfall changing patterns projected under different RCP scenarios would be homogenized in the integration of various GCMs.

This study takes a building surrounded by 1000 m² green spaces and with 50 inhabitants living in it as an example. It should be noted that the areas of building roofs and green spaces, as well as the number of occupants and water use patterns are expected to change from place to place, which are assumed to be uniform in the four cities in this study.

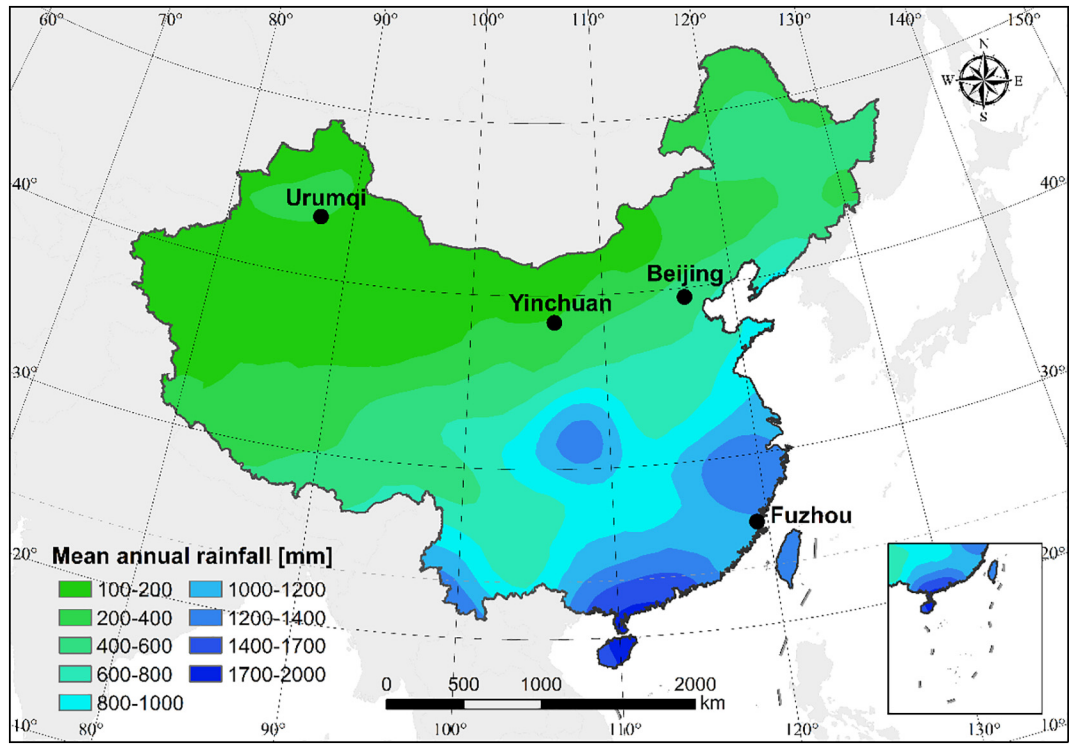


Fig. 1. Special distribution of mean annual rainfall of China and locations of the four cities [modified from Jing et al., 2017].

Rainwater from the building roof or other impervious areas, after bypassing first flush, can be collected for outdoor uses (i.e., irrigating the green space) or indoor uses (i.e., flushing toilets or urinals). Considering water efficient toilets, the toilet flushing water demand for a multi-storey residential building is 32 L per person per day (DB11/685, 2013). The frequency and quota of green space irrigation depends on types of plants, soil properties and climatic conditions (Table 1). In order to estimate the irrigation demand of the green space, mean monthly reference evapotranspiration at the four cities are determined using the CROPWAT 8.0 software (Allen et al., 1998). Details about the calculation procedures for daily toilet flushing water demand for the building and the frequency and quota of green space irrigation can be found in Jing et al. (2017) and Zhang et al. (2018). It should be noted that water demand, average number of inhabitants and water use patterns are expected to change with time, which however is difficult to predict (Haque et al., 2016; Campisano et al., 2017), and hence kept fixed in this study.

2.2. Water balance model of RWH systems

The daily water balance model developed by Jing et al. (2017) and Zhang et al. (2018) is employed in this study. The model is based on the “yield after spillage” (YAS) operating rule (Fewkes and Butler, 2000; Jing et al., 2018) and expressed as

$$I_t = \begin{cases} 0, & H_t \leq \delta \\ \frac{\psi(H_t - \delta)F}{1000}, & H_t > \delta \end{cases} \quad (1)$$

$$Y_t = \begin{cases} R_{t-1} + I_t, & R_{t-1} + I_t - D_t \leq 0 \\ D_t, & R_{t-1} + I_t - D_t > 0 \end{cases} \quad (2)$$

$$R_t = \begin{cases} R_{t-1} + I_t - Y_t, & R_{t-1} + I_t - S_c \leq 0 \\ S_c - Y_t, & R_{t-1} + I_t - S_c > 0 \end{cases} \quad (3)$$

where I_t is volume of runoff generated from the contributing areas on the t th day, in m^3 ; H_t is rainfall depth on the t th day, in mm; ψ is runoff coefficient, dimensionless; F is area of the contributing areas, in m^2 ; δ is volume of first flush over the contributing areas, in mm; Y_t is volume of rainwater yield on the t th day, in m^3 ; D_t is water demand on the t th day, in m^3 ; R_t is volume of rainwater remained in the tank or cistern at the end of the t th day, in m^3 ; S_c is the storage capacity, in m^3 .

The water saving performance of RWH systems can be evaluated using water saving efficiency and time reliability as presented in Wallace et al. (2015) and Haque et al. (2016). The water saving efficiency (WSE, %) is defined as the ratio of the total amount of water supplied from the RWH system and the total amount of water demand, and it is calculated as,

$$\text{WSE} = \frac{\sum Y_t}{\sum D_t} \times 100\% \quad (4)$$

The time reliability (r , %) is defined as the portion of time that the RWH system will meet water demand, and it is calculated as,

$$r = \frac{M}{N} \times 100\% \quad (5)$$

where M is the total number of days the RWH system is able to meet the water demand (i.e., $R_{t-1} + I_t \geq D_t$), and N is the total number of days of the simulation period.

Stormwater volume control performance of RWH systems can be indicated by stormwater capture efficiency, as demonstrated in previous studies for other LID practices such as green roofs (Zhang and Guo, 2013a), rain gardens (Zhang and Guo, 2013b), bioretention systems (Zhang and Guo, 2014), and permeable pavement systems (Zhang and Guo, 2015). The stormwater capture efficiency (SCE, %) of the RWH system is defined as the fraction of stormwater generated from the contributing catchments which is

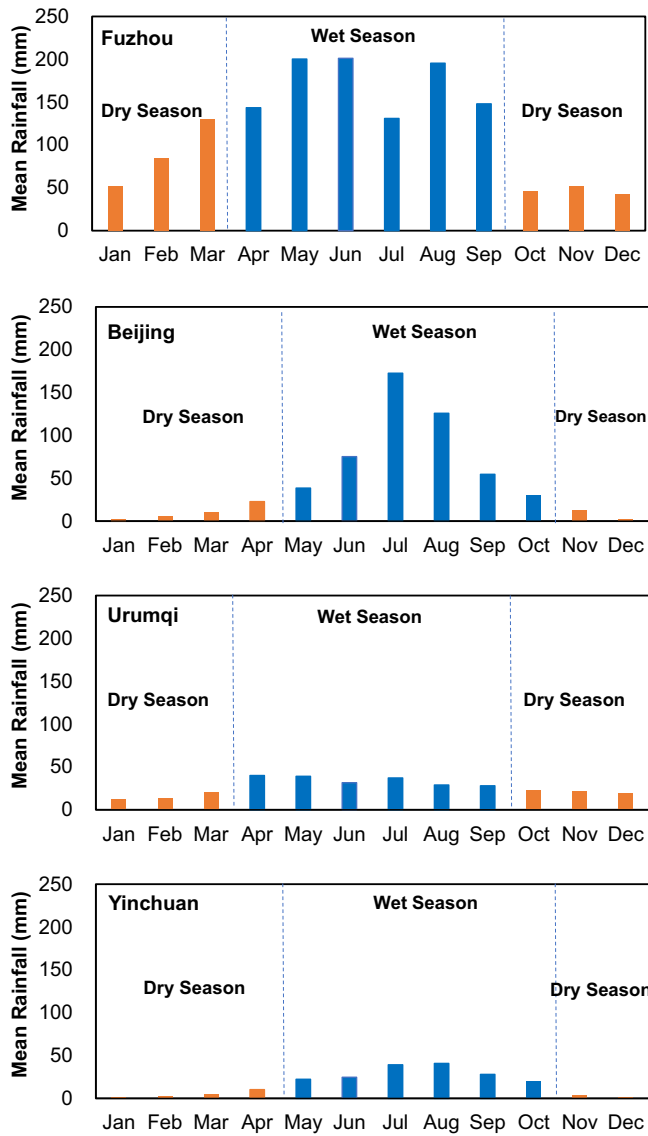


Fig. 2. Mean monthly rainfall at the four cities from 1960 to 2015.

captured by the system and utilized to satisfy water demands, and can be calculated as

$$SCE = \frac{\sum Y_t}{\psi A \sum H_t / 1000} \times 100\% \quad (6)$$

Table 1

Irrigation frequency and quota of lawns at Fuzhou, Beijing, Urumqi, and Yinchuan.

Month	Fuzhou		Beijing		Urumqi		Yinchuan	
	Irrigation frequency	Average daily quota (m ³ /d)	Irrigation frequency	Average daily quota (m ³ /d)	Irrigation frequency	Average daily quota (m ³ /d)	Irrigation frequency	Average daily quota (m ³ /d)
Jan	None	0	None	0	None	0	None	0
Feb	None	0	None	0	None	0	None	0
Mar	Monthly	0.05	Fortnightly	0.16	Monthly	0.03	Monthly	0.07
Apr	Fortnightly	0.14	Every 5 days	0.79	Fortnightly	0.20	Every 3 days	0.83
May	Fortnightly	0.15	Every 3 days	1.11	Every 3 days	1.02	Alternate days	2.20
Jun	Every 5 days	0.56	Every 3 days	1.20	Every 2 days	1.77	Alternate days	2.46
Jul	Every 5 days	0.74	Every 3 days	0.95	Every 2 days	1.80	Alternate days	2.28
Aug	Every 5 days	0.72	Every 5 days	0.72	Every 2 days	1.74	Every 3 days	0.93
Sep	Fortnightly	0.20	Weekly	0.45	Every 5 days	0.76	Weekly	0.42
Oct	Monthly	0.08	Fortnightly	0.16	Monthly	0.09	Monthly	0.07
Nov	None	0	None	0	None	0	None	0
Dec	None	0	None	0	None	0	None	0

2.3. Downscaling of GCM projected climate data

In order to drive the water balance model of RWH systems, the monthly rainfall data at grid scale ($1^\circ \times 1^\circ$) projected by GCMs needs to be downscaled to appropriate spatial and temporal resolutions. Stochastic weather generators, such as the Weather Generator (WGEN), the Climate Generator (CLIGEN), and the Long Ashton Research Station Weather Generator (LARS-WG), have often been used as downscaling tools to produce high-resolution climate data by linking their parameters to climate model outputs (Yu, 2005; Zhang, 2007; Cowden et al., 2008; Zhang et al., 2010). In this study, the CLIGEN model (Nicks et al., 1995) which generates the occurrence of daily rainfall using a first-order, two-state Markov chain is employed for the downscaling of future climate data. The Markov chain generates daily rainfall based on transition probabilities of a wet day following a wet day ($P_{w/w}$) and a wet day following a dry day ($P_{w/d}$). The daily mean rainfall (R_d , mm) is generated using a skewed normal distribution.

2.3.1. Spatial downscaling of future climate data

Spatial downscaling is to downscale the monthly GCMs projections at $1^\circ \times 1^\circ$ grid boxes to monthly values at specific weather stations using transfer functions. The transfer functions are fitted using the GCM projected monthly rainfall of 1960–2005 at the grid boxes in conjunction with the monthly data of the same period measured at the four cities (stations) for each calendar month. The measured and GCM-projected monthly rainfall of 1960–2005 at each station is ranked for each calendar month. The ranked GCM-projected monthly rainfall is plotted with the ranked measured monthly rainfall. Both a nonlinear and a linear functions are fitted to each plot for each calendar month at each station. Those fitted transfer functions are employed to downscale the 2020–2050 monthly rainfall at the $1^\circ \times 1^\circ$ GCM scale boxes to those at the four weather stations with an assumption that those fitted functions are suitable in the changed climate (Zhang, 2007).

For each calendar month, the downscaled monthly rainfall values are used to calculate the mean and variance of monthly rainfall in the changed climate. The mean and variance of each calendar month are used to estimate the mean and variance of daily rainfall, which are required input parameters to the CLIGEN model for generating daily rainfall series of 2020–2050.

2.3.2. Temporal downscaling of future climate data

Temporal downscaling is to estimate CLIGEN input parameters used to generate daily rainfall series representing the future climate. Measured daily rainfall data of 1960–2005 at each of the four stations are used to calculate the baseline input parameters for the CLIGEN model. These baseline input parameters are then adjusted to generate the daily rainfall series of 2020–2050 for the stations. Four rainfall parameters require adjustments for running the CLIGEN model to generate

future daily rainfall series [i.e., R_d , $P_{w/w}$, $P_{w/d}$, and variance of daily rainfall (σ_d^2)].

For the adjustments of transition probabilities (i.e., $P_{w/w}$ and $P_{w/d}$), linear functions between mean monthly rainfall (R_m) and the transition probabilities are established for each calendar month with the historical records. For each calendar month, the 46 months (1960–2005) are equally separated into wettest and driest groups (i.e., 23 months in each group). $P_{w/w}$, $P_{w/d}$ and R_m are calculated for each group. Based on the $P_{w/w}$, $P_{w/d}$ and R_m values for the wettest and driest groups, linear functions between $P_{w/w}$ and R_m as well as between $P_{w/d}$ and R_m are developed for each calendar month. Based on the relationships, the adjusted $P_{w/w}$ and $P_{w/d}$ for the changed climate can be linearly interpolated with the downscaled R_m .

The adjustments of mean daily rainfall per wet day (R_d) and variance of daily rainfall (σ_d^2) can be done using the following equations (Wilks, 1999; Zhang, 2007).

$$R_d = \frac{R_m}{N_d \pi} \quad (7)$$

$$\sigma_d^2 = \frac{\sigma_m^2}{N_d \pi} - \frac{(1-\pi)(1 + P_{w/w} - P_{w/d})}{1 - P_{w/w} + P_{w/d}} R_d^2 \quad (8)$$

$$\pi = \frac{P_{w/d}}{1 + P_{w/d} - P_{w/w}} \quad (9)$$

where N_d is the number of days in the month and π is the unconditional probability of daily rainfall occurrence.

Using the spatial and temporal downscaling methods, the projected future monthly rainfall data at grid scale in the 2020–2050 period under the RCP2.6, RCP4.5, and RCP8.5 scenarios are downscaled to daily rainfall at station scale. In the following sections, only the results under the RCP4.5 scenario are analyzed and compared with that in the historical period, as no obvious differences are found among the water saving or stormwater management performances of RWH systems in the 2020–2050 period under the three climate change scenarios (Appendix B). This is possibly caused by two reasons: (1) the arithmetic ensemble mean of 21 GCMs outputs is used in this study and the differences among future rainfall patterns projected under different climate change scenarios by a single GCM could be homogenized in the ensemble mean; (2) though the RCP2.6 is the lowest emission scenario, it shows an increase in radiative forcing to a peak value around 3.1 W/m² by mid-century, and then reduces to 2.6 W/m² by 2100 (Van Vuuren et al., 2011), which could also have a significant effect on climate patterns in the period of 2020–2050 (Wallace et al., 2015).

3. Results and discussions

3.1. Downscaling of GCM projected rainfall data

Linear and nonlinear regressions between the ranked GCM-projected monthly rainfall at grid scale versus the corresponding measured monthly rainfall at station scale are carried out for each calendar month at the four stations for the period of 1960–2005. The determination coefficients (R^2) of the nonlinear regressions range from 0.904 to 0.994 with an average value of 0.976, and those for the linear regressions range from 0.494 to 0.979 with an average value of 0.860 (Table 2). The large values of R^2 indicate that those transform functions, especially the nonlinear ones, are expected to perform well in reproducing probability distributions of measured monthly rainfall data from the GCM-projected monthly rainfall. Fig. 3 shows the qq-plot for the spatially downscaled GCM monthly rainfall using the nonlinear transform functions versus the corresponding measured monthly rainfall of 1960–2005. It further demonstrates how well the fitted functions perform in reproducing the probability distributions of monthly rainfall.

The CLIGEN model generated and measured monthly means and standard deviations of number of wet days for each calendar month at the four cities for the period of 1960–2005 are plotted in Fig. 4. The errors of monthly means of number of wet days range from −0.89 to 0.61 days. The errors of monthly standard deviations of number of wet days range from −1.26 to 1.03 days. These small errors in both means and standard deviations of number of wet days indicate that the occurrence of daily rainfall at the four cities is well simulated by the CLIGEN model.

The nonparametric Kolmogorov–Smirnov (K–S) test is employed to test the identity of the measured and CLIGEN generated probability distributions of daily rainfall for each calendar month. As presented in Table 3, altogether 33 out of the 48 month–location combinations (i.e., 68.8%) passed the K–S test at the significance level of 0.05. The CLIGEN model performs the best at Fuzhou with ten calendar months (i.e., 83.3%) passing the K–S test. At Yinchuan, however, half of calendar months (i.e., 50.0%) could not pass the K–S test. Similar K–S test results were reported by Zhang et al. (2008) for 6 stations in the semi-arid Loess Plateau of China. The frequency distributions of daily rainfall from the Measured and CLIGEN generated data for calendar months with the largest and smallest P values in the K–S test at each of the four cities are displayed in Fig. 5. It further demonstrates that the CLIGEN model could reproduce the probability distributions of daily rainfall well at Fuzhou, Beijing and Urumqi. In the arid city Yinchuan, the probability distributions of daily rainfall could only be well simulated by the CLIGEN model in the months from May to October, which just happen to make up the wet season of the city. As shown in Figs. 2, 87.4% of the mean annual rainfall at Yinchuan falls in the wet season. Therefore, the CLIGEN model could alternatively be used at Yinchuan for RWH system analysis.

Table 2

Determination coefficients (R^2) of the transfer functions between GCM projected monthly rainfall at the grid scale and measured monthly rainfall for the period of 1960–2005.

Month	Fuzhou		Beijing		Urumqi		Yinchuan	
	Linear	Nonlinear	Linear	Nonlinear	Linear	Nonlinear	Linear	Nonlinear
Jan	0.848	0.993	0.909	0.972	0.929	0.978	0.524	0.991
Feb	0.908	0.953	0.875	0.980	0.867	0.973	0.494	0.987
Mar	0.906	0.959	0.947	0.992	0.978	0.904	0.707	0.986
Apr	0.965	0.984	0.804	0.990	0.978	0.964	0.780	0.978
May	0.979	0.986	0.933	0.964	0.928	0.987	0.855	0.982
Jun	0.970	0.980	0.922	0.980	0.878	0.969	0.768	0.974
Jul	0.922	0.971	0.978	0.983	0.879	0.989	0.945	0.994
Aug	0.847	0.957	0.833	0.954	0.831	0.978	0.902	0.982
Sep	0.921	0.971	0.874	0.972	0.960	0.982	0.891	0.990
Oct	0.839	0.982	0.728	0.985	0.926	0.984	0.796	0.975
Nov	0.829	0.982	0.815	0.973	0.911	0.978	0.659	0.925
Dec	0.940	0.982	0.799	0.981	0.960	0.980	0.623	0.971

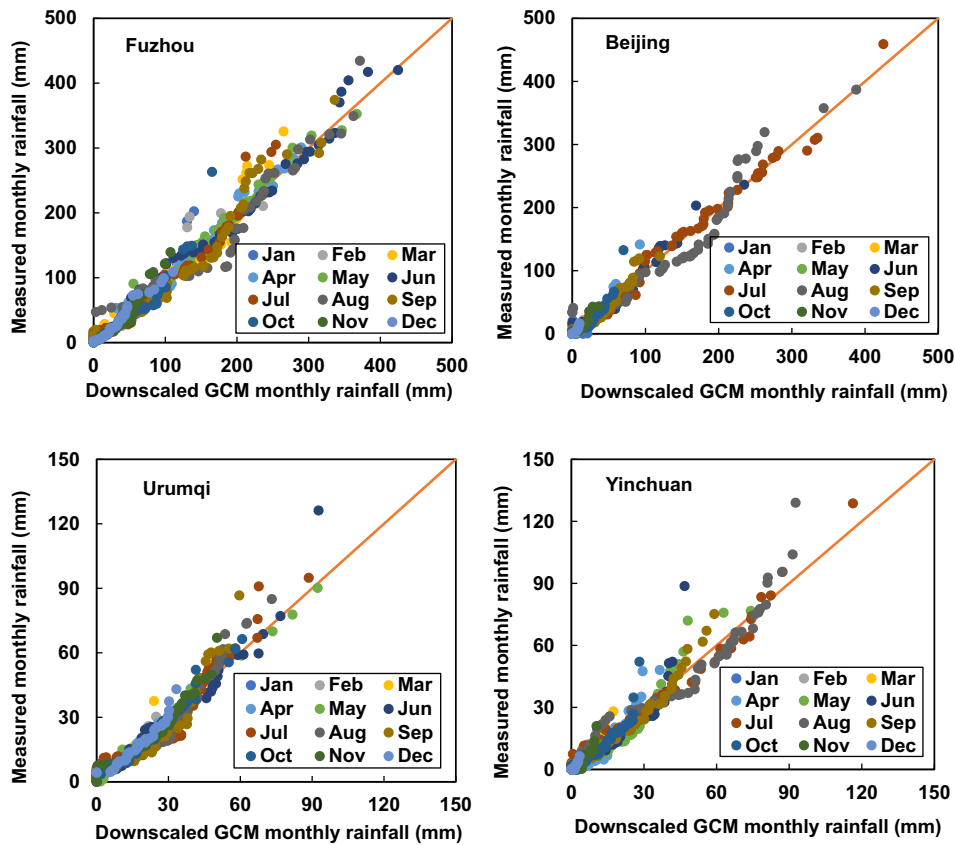


Fig. 3. QQ-plots of measured and spatially downscaled GCM monthly rainfall for the period of 1960–2005.

From Figs. 3–5 and Tables 2 and 3, it can be concluded that the CLIGEN based spatial and temporal downscaling methods can appropriately reproduce the occurrence and probability distributions of daily rainfall at the four cities. This downscaling technique is simple and sound, which has been validated and applied in many other regions of the world to assess the site-specific impacts of climate change on soil erosion and crop production (e.g., Zhang et al., 2010; Li et al., 2011; Lobo et al., 2015; Vaghefi and Yu, 2017).

3.2. Changes in annual and seasonal rainfall

The downscaled future rainfall during the 2020–2050 period are compared with measured rainfall of the 1985–2015 period, the results are shown in Fig. 6. The mean annual rainfall during the 2020–2050

period is projected to increase by 2.7%–62.0% at the four cities located in different climatic zones (Fig. 6a). Among the four cities, Beijing is expected to face the highest augment in rainfall with the mean annual rainfall increasing by 62.0% (338.2 mm), whereas the mean annual rainfall in Fuzhou only increases by 2.7% (38.1 mm). Yinchuan and Urumqi are projected to have 81.8 mm and 86.3 mm more average annual rainfall, respectively, in the future period. The changing trends of rainfall at the four cities are consistent with the results presented by Xu and Xu (2012). Increases in rainfall are also expected in other Asian countries as South Korea (Youn et al., 2012) and Sri Lanka (Lo and Koralegedara, 2015).

The seasonal changes of rainfall in the 2020–2050 period (Fig. 6b) indicate that the wet season would be wetter as average rainfall in wet season increased by around 3.9% to 62.7% at the four cities compared

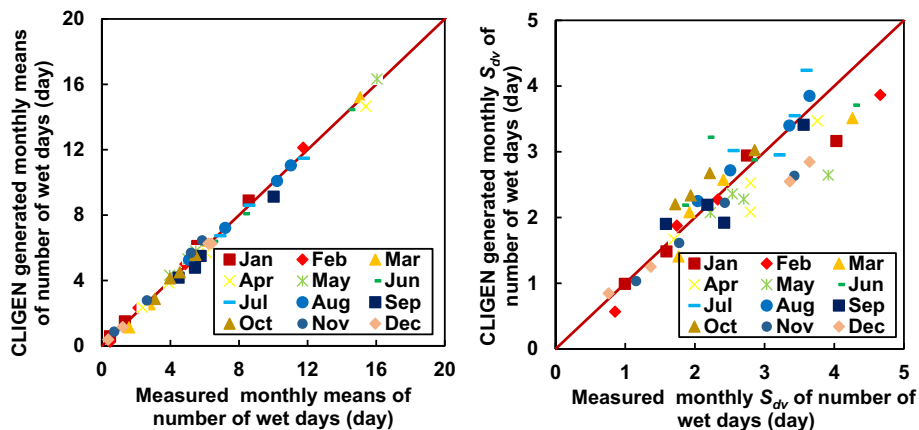


Fig. 4. Measured and CLIGEN generated monthly means and standard deviation (S_{dv}) of wet days at the four cities for the period of 1960–2005.

Table 3

P values of the Kolmogorov-Smirnov test for measured and CLIGEN generated daily rainfall.

Month	Fuzhou	Beijing	Urumqi	Yinchuan
Jan	<0.001	0.050	<0.001	0.685
Feb	0.239	0.663	0.085	0.650
Mar	<0.001	0.006	<0.001	0.436
Apr	0.007	0.151	0.011	0.169
May	<0.001	<0.001	0.004	<0.001
Jun	<0.001	<0.001	0.502	<0.001
Jul	<0.001	<0.001	<0.001	<0.001
Aug	<0.001	0.033	0.032	<0.001
Sep	<0.001	0.122	0.137	<0.001
Oct	<0.001	<0.001	0.002	0.013
Nov	0.013	<0.001	<0.001	0.417
Dec	0.143	0.055	<0.001	0.850

with the 1985–2015 period. The average rainfall in dry season at three of the cities is expected to increase by around 29.5%–92.8%, with an exception that a slight decrease in rainfall in dry season by 0.5% is expected in Fuzhou. The highest relative change (92.8%) in dry season at Yinchuan is resulted from an absolute increment of 22.2 mm divided by the relatively low average rainfall of 23.9 mm in dry seasons of the baseline period (1985–2015). The pattern of rainfall changes towards more uneven temporal distribution of rainfall is usually described by the phrase “dry gets drier, wet gets wetter” in climate change studies (e.g., [Chen et al., 2017](#)). The study of [Haque et al. \(2016\)](#) supports this rainfall changing pattern as the dry season is expected to be drier while the wet season would be wetter in future at the Sydney region. However, climate change has different effects in different areas, the “dry gets drier” pattern does not hold at all the four cities in this study as three of them are expected to have more rainfall in dry season.

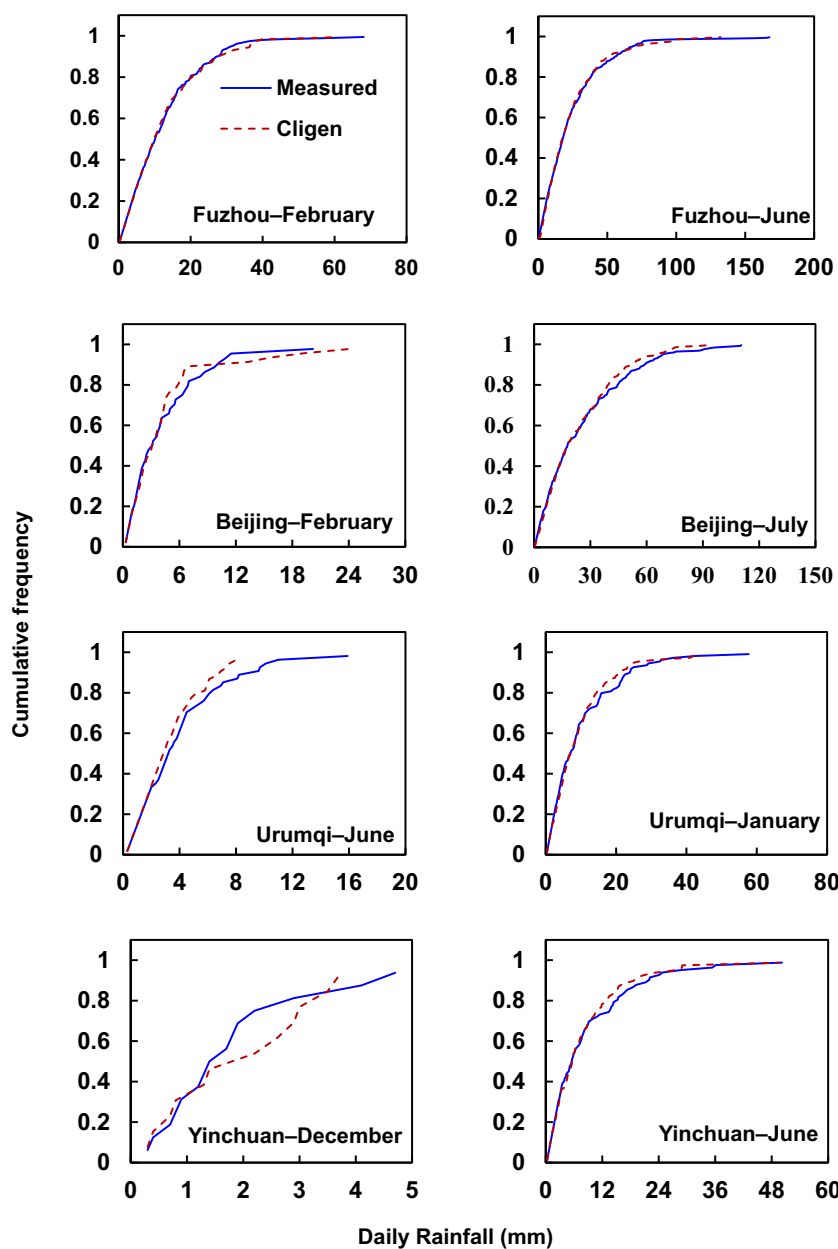


Fig. 5. Cumulative frequency distributions of daily rainfall from the Measured and CLIGEN generated data for the period of 1960–2005 (the worst fittings in the left column and the best fittings in the right column).

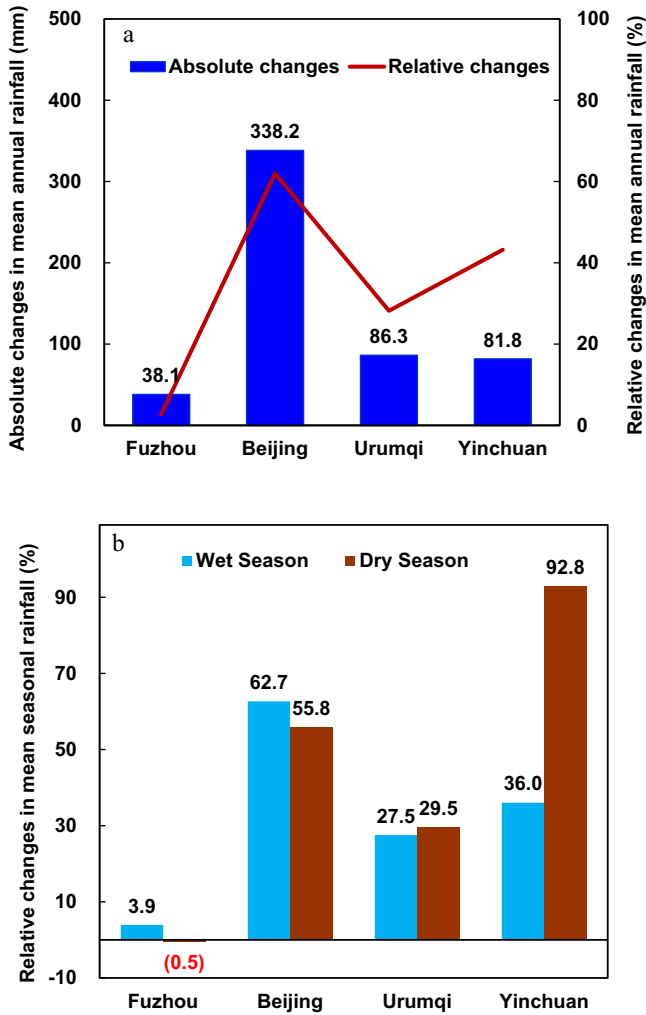


Fig. 6. Changes in mean rainfall in wet and dry seasons between the periods of 2020–2050 and 1985–2015 at the four cities.

3.3. Impacts on water savings of RWH systems

Water saving efficiency (WSE) of RWH systems for both indoor and outdoor demand scenarios is expected to increase at the four cities for the 2020–2050 period in comparison with the 1985–2015 period (Table 4). However, the changes in WSE are dependent on not only the water demand scenarios and storage capacity of the systems, but also the locations. For RWH systems with storage capacity varying

from 5 to 100 m³ and for both indoor and outdoor demand scenarios at the four cities, the relative changes in WSE range from −0.5% to 67.2%. These changes in WSE are interrelated with the 2.7%–62.0% increases in annual rainfall at the four cities as presented in Section 3.2.

The relative changes in WSE of RWH systems for indoor demand are mostly larger than outdoor demand. This is related to the fact that outdoor water demand (0.22 m³/day to 0.77 m³/day) is less than the indoor water demand (1.60 m³/day) for all the four cities, as a result, the WSE of RWH systems for outdoor demand is larger than that for indoor demand in the historical period. The larger WSE for outdoor demand makes relatively less room for increasing in the future period. For example, the WSE of a 50m³ RWH system supplying water for lawn irrigation at Beijing is 96.2% in the 1985–2015 period, and this value cannot be increased by >3.8% no matter how much rainfall is available. However, for indoor demand, the WSE of this system is only 43.1%, which still has much room for rising given the increases in rainwater in the future period.

The relative changes in WSE decreases with storage capacity for both indoor and outdoor demand scenarios at all the cities. It indicates that a RWH system with larger storage capacity can have better water saving performances and is expected to be more resilient to climate change. This finding is consistent with results presented by Youn et al. (2012) and Haque et al. (2016). The relative changes in WSE of RWH systems under the same water demand scenario and with the same storage capacity at the four cities are in an almost opposite order with the mean annual rainfall at the cities. It indicates that RWH systems at cities with less rainfall (e.g., Urumqi and Yinchuan) are relatively more sensitive to climate changes. For instance, the relative changes in WSE of a 5 m³ RWH system harvesting rainwater for indoor demand at Urumqi and Yinchuan are 47.8% and 67.2%, respectively, which are obviously higher than that at Fuzhou and Beijing (14.7% and 38.7%, respectively).

The WSE in wet and dry seasons for the two water demand scenarios in the future and historical periods is presented in Table 5. For indoor demand, which has a constant water use rate in both wet and dry seasons, WSE is much higher in wet season than dry season for all the cities. For example, the WSE in wet season at Urumqi during the 1985–2015 period is 42.4%, which is more than twice that in dry season (17.8%). The higher WSE in wet season is related to more rainfall in wet season than dry season. Rainfall in wet season accounts for 65.4%–91.2% of the mean annual rainfall at the four cities. For outdoor demand, WSE is higher in wet season at Fuzhou and Beijing, in contrast, it is lower in wet season at Urumqi and Yinchuan. The reason for the higher WSE in wet season at Fuzhou and Beijing is probably that these two cities are both located in monsoon climate zone and have plenty of rainwater to meet the relatively lower lawn irrigation demand in wet season. While the relatively higher WSE in dry season at Urumqi and Yinchuan is likely related to the fact that no water is needed for lawn irrigation in

Table 4
Changes in water saving efficiency in the future period for RWH systems with 1000 m² catchment area (%).

Storage capacity (m ³)	Fuzhou		Beijing		Urumqi		Yinchuan	
	1985–2015	2020–2050	1985–2015	2020–2050	1985–2015	2020–2050	1985–2015	2020–2050
Indoor demand								
5	39.5	45.3 (14.7)	19.2	26.7 (38.7)	16.5	24.4 (47.8)	9.3	15.6 (67.2)
10	54.3	61.8 (13.7)	27.4	36.6 (34.0)	22.9	30.5 (33.1)	13.4	21.2 (58.4)
20	68.2	75.7 (11.0)	35.2	45.4 (28.8)	27.9	34.2 (22.7)	17.1	25.6 (50.2)
50	83.0	87.9 (6.0)	43.1	52.9 (22.9)	30.8	36.1 (17.3)	19.5	28.4 (45.6)
100	92.1	96.0 (4.3)	50.8	61.2 (20.5)	31.1	36.2 (16.6)	20.5	28.8 (40.7)
Outdoor demand								
5	79.4	84.3 (6.2)	51.0	65.5 (28.4)	25.3	37.7 (48.9)	17.3	25.7 (48.7)
10	92.9	94.3 (1.5)	67.8	82.0 (21.0)	35.1	48.5 (38.1)	25.0	36.1 (44.4)
20	99.7	99.2 (−0.5)	82.1	92.3 (12.5)	45.7	57.7 (26.1)	32.2	45.0 (39.4)
50	100.0	100.0 (0.0)	96.2	99.0 (3.0)	62.1	72.1 (16.1)	38.9	54.5 (40.2)
100	100.0	100.0 (0.0)	98.9	99.4 (0.5)	76.2	87.6 (15.0)	41.2	58.4 (41.9)

Note: Bold numbers in the brackets are relative changes in water saving efficiency between 1985–2015 and 2020–2050.

Table 5Water saving efficiency in wet and dry seasons for a RWH system with 50 m³ storage capacity and 1000 m² catchment area (%).

	Wet season			Dry season		
	1985–2015	2020–2050	Relative changes	1985–2015	2020–2050	Relative changes
Indoor demand						
Fuzhou	95.9	96.4	0.5	59.7	65.5	9.7
Beijing	73.7	85.3	15.7	9.5	14.3	51.6
Urumqi	42.4	52.5	23.8	17.8	19.0	6.9
Yinchuan	34.7	48.6	40.0	3.9	7.4	89.0
Outdoor demand						
Fuzhou	100.0	100.0	0.0	71.3	72.5	1.6
Beijing	80.6	86.6	7.5	71.5	88.8	24.2
Urumqi	52.5	65.3	24.4	70.4	82.9	17.7
Yinchuan	30.8	41.1	33.6	35.4	65.4	84.5

4 months (November to February) of dry season at these two cities (Table 1).

The changes in *WSE* between the future and historical periods show that it would increase in the 2020–2050 period in both wet and dry seasons and for both water demand scenarios at the four cities. For indoor demand, *WSE* is going to increase by 0.5%–40.0% in wet season and to increase by 6.9%–89.6% in dry season in the future period. For outdoor demand, the relative changes are 0–33.6% and 1.6%–84.5% in wet and dry seasons, respectively. The increases in *WSE* in wet and dry seasons are in correlation with the changing patterns of seasonal rainfall as mentioned earlier. For instance, the highest relative changes in dry season rainfall at Yinchuan (92.8%) is likely to be the reason that the largest relative changes of *WSE* in dry season for indoor and outdoor water demand scenarios (89.0% and 84.5%, respectively) are both found at Yinchuan.

3.4. Impacts on reliability of RWH systems

Design curves comprising the ensembles of storage capacity and catchment area combinations that yield a given level of reliability (e.g., 50%, 80%) are developed and shown in Fig. 7 using the future and historical rainfall data. In general, the design curves shift not only among water demand scenarios and locations, but also with the future and historical rainfall conditions. Regardless of these factors, however, the design curves corresponding to higher level of reliability (e.g., 80%) are shifting up and to the right of those with lower level of reliability (e.g., 50%). These findings are incoherent with curves developed using historical rainfall data (Fewkes and Butler, 2000) and downscaled GCM projections (Wallace et al., 2015). It is reasonable that higher requirements in water supply reliability of RWH systems need larger tanks to harvest rainwater from roof catchment with larger areas.

The system dimensions (storage capacity and catchment area) required to achieve a desired level of reliability are higher for the cities with less rainfall. Furthermore, the design curves with different reliability rates are more clustered in Fuzhou and Beijing, while that are more dispersed for Urumqi and Yinchuan. Relatively high levels of rainfall in the humid and semi-humid cities (e.g., Fuzhou and Beijing) allow for smaller system dimensions when compared to systems in arid and semi-arid regions (e.g., Urumqi and Yinchuan) at the same rate of reliability (Basinger et al., 2010). For all the cities, the design curves with different reliability rates are more dispersed and shift up and to the right in the figures for the indoor demand (i.e., the left column of Fig. 7) in comparison with the outdoor demand (i.e., the right column of Fig. 7). It indicates that larger storage capacity and catchment areas are usually required to achieve a same desired level of reliability for larger water demand scenarios. For example, harvesting rainwater from 1000 m² roof catchment at Beijing in the 2020–2050 period requires only 4m³ tanks for outdoor demand to meet the 80% reliability rate. For the indoor demand, however, the corresponding requirement of storage size is 239m³, which is dozens of times larger than that for the outdoor demand.

The design curves with different reliability rates developed using the future rainfall data are shifting down and to the left of the corresponding ones developed using the historical rainfall data for both indoor and outdoor water demand scenarios at all the four cities. It is interrelated with the projected increases in rainfall at the cities. Increased rainfall in the future period makes it easier to harvest adequate rainwater with a smaller tank size from a smaller roof catchment. The design curves with a same reliability rate developed using both the 2020–2050 and 1985–2015 rainfall data are generally more dispersed for larger water demand scenarios and in cities with less rainfall. It implies that the reliability of RWH systems in the arid and semi-arid cities are more sensitive to climate change than that in the humid and semi-humid cities. The design curves with a same reliability rate (e.g., 80% or 50%) developed using both the 2020–2050 and 1985–2015 rainfall data at Beijing are more spread than that at Urumqi, because Beijing is expected to face higher augment in annual rainfall than Urumqi.

The reliability levels of 50% and 80%, which represent relatively moderate and high water supply requirements, respectively, are just used as examples to illustrate the impacts of climate change on the design curves of RWH systems. Reliability of RWH systems is determined by not only the system dimensions such as storage capacity and catchment area, but also the site conditions of the systems such as rainfall and water demand scenarios (Imteaz et al., 2011). It changes from place to place. Various reliability levels have been used in different studies. For instance, Liaw and Tsai (2004) used a reliability level of 90% to develop design curves by which optimal cistern sizes could be selected at Hsinchu County in Taiwan. Basinger et al. (2010) used different levels of reliability (5%–95% for toilet flushing, 85%–95% for garden irrigation, and 75%–95% for air conditioning water demand) to develop design curves for different water demand scenarios. Khastagir and Jayasuriya (2010) investigated the variation of optimum tank sizes of RWH for a water supply reliability of 90% in the Greater Melbourne area. Wallace et al. (2015) used reliability levels of 80%, 90%, and 95% to develop design curves for RWH systems located in two climatic regions of the Federated States of Micronesia.

3.5. Impacts on stormwater capture efficiency of RWH systems

Many municipalities have specific stormwater volume control requirements on new sites development and old sites restoration. In Beijing, for instance, the municipality requires that the runoff coefficients of new districts and old towns should be <0.4 and 0.5, respectively (DB11/685, 2013). To meet these stormwater volume control requirements, the stormwater capture efficiency (*SCE*) of RWH systems in new districts and old towns should be not <60% and 50%, respectively.

The ensembles of storage capacity and catchment area combinations required to achieve the 50% and 60% *SCE* are determined using the future and historical rainfall data (Fig. 8). Similar to the design curves for various reliability rates, the curves corresponding to different *SCE* also shift with factors such as the water demand scenarios, locations, and rainfall conditions. In contrast, the curves corresponding to higher

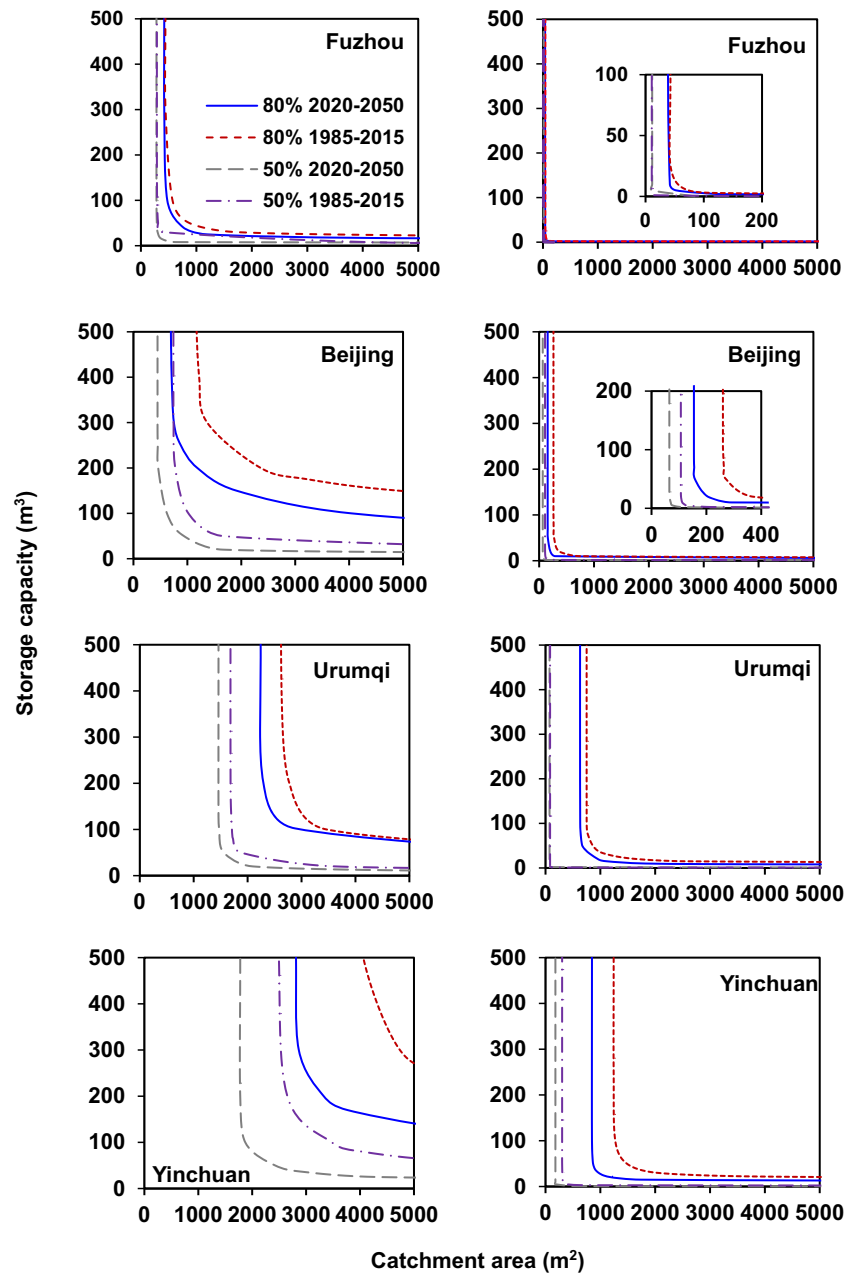


Fig. 7. Reliability of RWH systems at the four cities for the periods of 2020–2050 and 1985–2015 (indoor demand in the left column and outdoor demand in the right column).

SCE (e.g., 60%) are shifting up and to the left of those with lower SCE (e.g., 50%). It is because larger tanks are required to capture more stormwater generated from a given catchment area so that the higher SCE could be achieved.

The curves are more clustered to the left parts of the figures in cities with more rainfall and for outdoor water demand (i.e., the right column of Fig. 8). It indicates that RWH systems with a given tank size and less water demand can be used to control runoff generated from smaller roof catchments in cities with more rainfall. For example, to satisfy the 50% SCE requirement, a 50m³ RWH system for indoor or outdoor demands in Fuzhou can manage runoff generated from roof catchments with areas of 703 m² and 126 m², respectively. In Yinchuan, the suitable roof catchment areas in this situation are enlarged to 2553 m² and 1893 m², respectively. The larger values of suitable catchment areas at those two cities are both corresponding to larger water demand scenario. It demonstrates that the stormwater volume control performance of RWH systems is demand-driven (Petrucci et al., 2012), and the

magnitude of water demand can significantly influence the stormwater management performance of the systems (Campisano et al., 2017).

The curves of both 50% and 60% SCE determined using the future rainfall data shift to the left of the corresponding ones developed using the historical rainfall data for both indoor and outdoor demand scenarios at all the cities. It means that a RWH system with a given storage capacity is likely to capture less percentage of stormwater generated from the same roof catchment in the future, regardless of the locations and water demand scenarios. The projected increases in annual rainfall in the 2020–2050 period at the cities would certainly bring more challenges in stormwater management. For example, a 100m³ RWH system for indoor demand in Beijing could capture about 60% of stormwater generated from a 1000 m² roof catchment in the period of 1985–2015. In the 2020–2050 period, however, the SCE of this system would drop down to 44.9%. While the 60% SCE could still be achievable in 2020–2050, if the storage capacity of the system is enlarged to about 230 m³, which is more than twice of the original tank

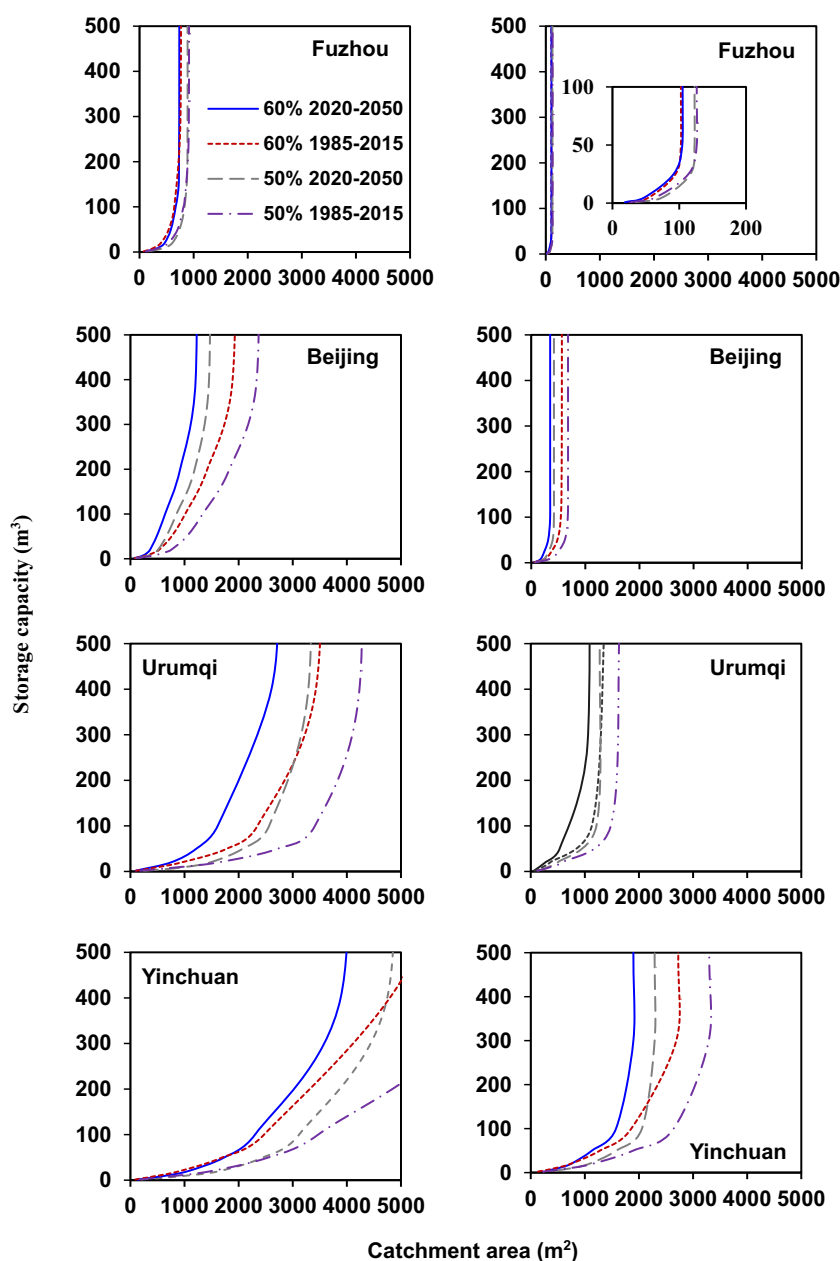


Fig. 8. Stormwater capture efficiency of RWH systems at the four cities for 2020–2050 and 1985–2015 (indoor demand in the left column and outdoor demand in the right column).

size. The variation in tank size for RWH systems to achieve a desired SCE in the future period highlights the need for RWH system design based on projected changes in climate. Similar to the changes in reliability,

the curves with a same SCE developed using the 2020–2050 and 1985–2015 rainfall data are generally more dispersed for indoor water demand and in cities with less rainfall. It implies that RWH systems

Table 6

Stormwater capture efficiency in wet and dry seasons for a RWH system with 50 m³ storage capacity and 1000 m² catchment area (%).

	Wet season			Dry season		
	1985–2015	2020–2050	Relative changes	1985–2015	2020–2050	Relative changes
Indoor demand						
Fuzhou	30.6	29.6	−3.4	47.7	52.7	10.5
Beijing	49.2	35.0	−28.8	54.5	53.0	−2.7
Urumqi	69.9	67.8	−3.0	53.2	44.0	−17.3
Yinchuan	68.6	70.6	2.9	53.1	52.1	−2.0
Outdoor demand						
Fuzhou	8.4	8.1	−3.9	0.78	0.80	2.3
Beijing	25.7	17.0	−33.9	40.7	32.4	−20.3
Urumqi	66.0	64.3	−2.5	2.7	2.4	−8.9
Yinchuan	52.9	51.9	−1.8	44.6	42.7	−4.3

are likely to be impacted more in the arid and semi-arid cities than in the humid and semi-humid cities for larger water demand scenarios.

The SCE of a RWH system with 50m³ storage capacity and 1000 m² catchment area in wet and dry seasons in the periods of 1985–2015 and 2020–2050 is presented in Table 6. In wet season, SCE in the 2020–2050 period decreases by 3.0%–28.8% and 1.8%–33.9% for indoor and outdoor demand scenarios, respectively, with the largest decreases for both indoor and outdoor demand scenarios appearing at Beijing. As aforementioned, Beijing is projected to face the largest increase in rainfall in wet season (62.7%). Therefore, the SCE in wet season at Beijing is expected to be impacted the most. In dry season, the SCE for both indoor and outdoor demand scenarios is also expected to reduce (by 2.0%–17.3% and 4.3%–20.3%, respectively) at all the cities except Fuzhou, as it would experience a slight decrease (–0.5%) in rainfall in dry season.

4. Conclusions and recommendations

Mean annual rainfall of the four cities (i.e., Fuzhou, Beijing, Urumqi, and Yichuan) in the 2020–2050 period is projected to increase by 2.7%–62.0% in comparison with the period of 1985–2015. Rainfall in both dry and wet seasons is projected to increase at all the cities by 3.9% to 92.8%, except in Fuzhou where rainfall in dry season decreases slightly (0.5%). Water saving performance of rainwater harvesting (RWH) systems at all the cities is positively affected by the increase in rainfall, as both water saving efficiency and reliability are increasing in the future period. With the increases in future rainfall, RWH systems with smaller tank sizes and smaller contributing catchments could supply adequate water at a desired water saving efficiency or reliability rate. Stormwater management performance of RWH systems, however, is negatively affected at all the cities. A larger tank size is required to achieve a desired stormwater capture efficiency in the future period for a given catchment area.

The impacts of climate change on water saving efficiency, reliability, and stormwater capture efficiency of RWH systems are dependent on not only the system dimensions (i.e., storage capacity and catchment area), but also the water demand scenarios and locations. RWH systems with larger storage capacity is expected to be more resilient to climate change, in other words, the impacts of climate change on RWH systems could be remedied by using a larger tank for some cases. For instance, the relative changes in water saving efficiency of RWH systems for outdoor demand at Beijing will be reduced from 28.4% to 0.5% if the storage capacity is enlarged from 5m³ to 100m³. RWH systems are likely to be impacted more in the arid and semi-arid cities (i.e., Yinchuan and Urumqi) than in the humid and semi-humid cities (i.e., Fuzhou and Beijing) for larger water demand scenarios.

Based on the results of this study, the following recommendations can be derived. Future climate change should be considered in the design and planning of RWH systems so that the systems can sustainably meet water saving and stormwater management requirements under future climate conditions. Location-specific adaptive measures (e.g., adjusting tank sizes, catchment areas and/or water demand rates and promoting implementation of RWH systems at watershed scale) should be adopted to accommodate climate change. The design curves, comprising the ensembles of storage capacity and catchment area combinations that yield a desired reliability rate (e.g., 50%, 80%) or a required stormwater capture efficiency (e.g., 50%, 80%) based on the projected future rainfall data, can be used as an easy and reliable tool for RWH systems design and planning.

Besides climate change, the water demand scenarios in urban areas (e.g., green space irrigation and toilet flushing, clothes, car, and street washing) may also change in the future. It would be better if accurate predictions of future urban water demand (Herrera et al., 2010; Al-Zahrani and Abo-Monasar, 2015) could be incorporated in the assessment of future climate change impacts on the water saving and performances of RWH systems. Moreover, differentiated water demand standards, areas of green space, as well as average numbers of inhabitants of a residential

building in cities located in different climatic zones may also be used in future researches.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2019.02.135>.

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